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Investigation of Chaotic Fuzzy Logic-Based Optical Character Recognition Model for Application in the Education Sector Field

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Abstract

Optical Character Recognition (OCR) is a technology that enhances the accessibility and inclusivity of learning materials for students across various age groups and skills. OCR can transform physical materials such as textbooks, research papers, and handwritten notes into digital text files. OCR systems optimized for structured text (e.g., printed books) may not perform well in real-world educational settings where handwritten notes, mixed scripts, and annotations are common. A direct performance comparison between OCRCHA and Deep Learning (DL) models on large, diverse datasets could highlight its advantages and limitations. This enhances the availability of study materials for students. The presence of varied handwriting styles and inadequate scan quality presents challenges for the OCR model. A subfield of artificial intelligence known as fuzzy logic has the potential to address these challenges, especially within the education sector. This work introduces Chaotic Fuzzy Logic (OCRCHA), a distinctive OCR system architecture designed for learning environments, integrating chaotic Large Language Models (LLM) with fuzzy logic. The system utilizes a feed-forward network to improve performance, integrating fuzzy logic with chaotic theory to increase flexibility and response accuracy. The experimental outcomes demonstrate notable performance improvements, highlighted by enhancements in F1 score, accuracy, and recall. This study introduces an enhanced iteration of the OCRCHA system to achieve more reliable character identification and demonstrates its efficacy in optical English letter recognition.

Keywords: Education, Fuzzy logic, Optical character recognition, Handwriting recognition, Chaotic theory.

1 | Introduction

The ability for machines to imitate human intelligence has been an idle goal for many years. However, machine reading has gone from an impossible goal to a practical reality in the previous half-century. Optical Character

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Recognition (OCR), a system for detecting and recognizing text and characters, is currently among the most prominent uses of AI and pattern recognition technology. OCR systems abound in many applications [1].

Many applications rely on Handwritten Text Recognition (HTR), including effectively reading handwritten materials across many domains, digitizing historical documents, processing forms, and transcribing handwritten notes. Improving the precision of HTR offers a world of possibilities for retrieval and analysis by making searchable massive volumes of handwritten data. This is particularly significant regarding archival, educational, and research purposes. The strength of HTR is that it can connect analog and digital domains, facilitating the use of handwritten material in many different contexts by making it searchable and more accessible. Therefore, improving the efficiency of HTR is an important goal, and there is a great deal of a chance for growth in this area of study.

The educational system is shaped by the complex structure of mathematical expressions used to represent the environment and the dynamics of variables. This makes the correlation process quite challenging. Communication between educators and their students has always been casual, spoken conversations [2]. In the future, mathematical models will be able to understand people's judgments; these models will be described in a human-friendly, natural language based on fuzzy sets, and ambiguous, divergent, or otherwise incorrect criteria will be identified using these models. Automated decision-support systems may readily include fuzzy logic, which provides a solid foundation for models of human behaviors and decisions [3]. Accurate results may be achieved by including fuzziness in the original data component using a mathematical model [4]. When a student does well academically or satisfies the state-mandated educational requirements, it is seen as a good outcome in educational institutions [5]. Many people are paying attention to how important it is for kids to accomplish well in all areas since professional competition is becoming more severe every day [6]. Learning outcomes are documented via educational evaluation, which mostly employs quantitative indicators of knowledge based on certain criteria [7]. Skills, attitudes, and beliefs may all be measured in this way. Numerous attempts have been made to identify an appropriate model for applying the fuzzy set to the education domain [8]. The proposed approach aims to provide an innovative viewpoint on the current student learning system. The computational feasibility of the OCRCHA model for real-time educational applications is unclear without detailed system requirements. The authors should specify hardware needs (CPU, GPU, RAM) and processing time per character or page. If chaotic fuzzy logic increases complexity, its impact on inference speed must be assessed. A comparison with existing OCR models (e.g., Tesseract, deep-learning-based OCR) would clarify efficiency. Optimizations like model pruning or quantization should also be discovered to guarantee real-time performance in classroom settings.

Here are the key findings from this study:

I. Construct an innovative model tailored to the field of education specifically for handwriting recognition.

II. To manage complicated systems with unpredictable handwriting pictures, a hybrid of fuzzy logic and chaos theory called chaotic fuzzy logic may be used.

III. Make real-time adjustments to the model's output parameters using Fuzzy Logic.

IV. Show considerable evaluation metrics measures when comparing to the benchmark model.

The paper's outline follows: Section 2 surveys the research on OCR and Large Language Models (LLM). The proposed hybrid model's architecture and full method are enclosed in Section 3. Experiment details, including dataset descriptions and findings, are enclosed in Section 4. Section 5 concludes the article by summarizing the results and discussing the model's implications.

2 | Related Work

2.1 | Large Language Model

Large linguistic models LLMs, such as ChatGPT [9], ChatGLM [10], and LLaMA2-Chat [11], represent a change in many sectors by improving user experiences in a wide range of applications. Yet, they are still

limited to specific industries [12]. Here are a few examples: While Chatlaw helps lawyers understand complex legalese, legislation, and case laws, OceanGPT is primarily concerned with oceanography and how to utilize massive datasets for marine ecosystem study and conservation [13], [14]. When diagnosing and interpreting complicated medical issues, HuatuoGPT is all about patient care and medical diagnostics [15], [16]. For the financial industry, FinGPT examines investment plans, financial reporting, and market tendencies [17].

Furthermore, ArtGPT analyzes creative works to support the creative process, providing insight into the philosophy and history that connects technology with the arts [18]. In addition, a MathGPT can analyze and solve complicated mathematical problems [19], [20]. Each model shows the coordinated effort to tailor LLM abilities to particular domains, which successfully traverse the inherent complexity of applying AI to various professions. The significant change in LLM impacts towards customized and interactive learning environments has brought attention to the far-reaching consequences of chat-based handwriting recognition systems on student engagement and achievement in the classroom. The versatility of LLMs for both academic assistance and emotional involvement with students is further shown by other educational chatbots like Ada [21] and the Replika AI platform. In addition, the ongoing work on improving the model is highlighted by the fine-tuning of LLM for complex instructor replies in the BEA 2023 Shared Task [22]. Adapter tuning to pattern exploiting training (PET [23]), low-rank adaptation (LoRA [24]), and prefix and prompt tuning (P-tuning, P-tuning V2 [25]) are some of the fine-tuning techniques that have improved model customization while improving the flexibility and efficacy of LLMs particular domains with least modifications to the underlying variables. This paper used an embedding method to investigate Single-Valued Trapezoidal Neutrosophic Linear Equations (SVTrNLEs). The method converts the SVTrNLEs into equal crisp linear systems that can be solved using standard approaches. The solution was then achieved utilizing either the matrix inversion technique or the gradient descent optimization approach, both provided in PyTorch. The resilience and applicability of gradient-based optimization approaches were rigorously tested [38]. This study describes a new method of traffic flow management in IoT-driven smart cities that use AI-powered prediction models. As urbanization grows, effective traffic management becomes increasingly important for improving mobility and minimizing congestion. Our prediction models use Machine Learning (ML) algorithms to assess real-time traffic patterns and anticipate future congestion locations, drawing on large amounts of data from IoT sensors such as traffic cameras, GPS devices, and environmental monitors. The study combines historical traffic data with real-time inputs to develop a dynamic model that responds to changing conditions, allowing municipal planners and traffic control systems to make more educated judgments [26]. This study brings new knowledge to the table by outlining a systematic approach to defining the wicked problem, prioritizing subproblems using Multi-Attribute Decision-Making (MADM), and solving the most critical subdivision using Data Envelopment Analysis (DEA), a hard OR technique [27].

Arabic and Urdu are regional languages that have received little investigation. This article compares the most important Deep Learning (DL) approaches for recognizing Arabic-adapted scripts, such as Arabic and Urdu [28]. The suggested approach improves resistance to high-intensity speckled noise and contrast discrepancies found in genuine retinal pictures. The suggested approach improves the segmentation of fluid-filled. Regions that emerge in DME patients without relying on high gradients in OCT images. Simulations show a significant increase in the accuracy and efficiency of DME segmentation compared to conventional approaches [29]. The restricted minimum gathering node coverage technique was initially used to optimize collection node assortment, assuring full data coverage across network nodes while consuming the fewest resources possible [30]. This study is being undertaken to develop an effective advertising strategy based on social networks in the educational business area. This research was conducted objectively using a survey-exploratory technique [31].

Using handwritten words, the author presented Customized Siamese Convolutional Neural Networks (CSCNNs) for offline writer verification. Moreover, a mixed loss function differentiates distinct writers' handwriting styles more accurately [32]. The 2-Tuple Linguistic q-Rung Ortho-pair Fuzzy Sets (2TLq-ROFS) is a unique improvement in fuzzy set theories that may merge decision-makers quantitative assessment concepts with qualitative evaluation information [33]. To successfully estimate housing prices, this study

analyzes exploratory data analysis using ridge regression, Elastic Net regression, linear regression, Lasso regression, and ML with feature selection [34]. This paper presents a hybrid DL strategy that blends CNN with a Bi-directional Recurrent Neural Network, notably a Bi-directional Gated Recurrent Unit (Bi-GRU) and Bi-directional Long Short-Term Memory (Bi-LSTM) [35]. Our suggested technique was verified on the Essay dataset through a series of tests, and the empirical findings revealed its superiority over both ML and DL approaches for personality recognition [36]. This chapter examines the uses of shallow and DL in banking, marketing, and e-commerce. The pros and cons of each approach in various applications are discussed. Furthermore, tips on how to choose the best method are presented [37]. This report also highlights the limits of existing AI applications in special education, such as a paucity of intervention tools and the absence of standardized diagnostic procedures.

We use the Adaptive Fuzzy Inference System (ANFIS), driven by CRF and BERT algorithms, to automatically classify each item by training many unlabeled text data. The ANFIS model has language and numerical knowledge. It outperforms the ANN [38] regarding pattern recognition and data categorization. The suggested system used a method to address illumination differences in photos, including poor contrast distorted, darker, and brighter pictures. Simulations were conducted on a dataset of 200 photos. They attained a total detection accuracy of 95% with a very low Character Error Rate (CER) value of 0.0041, thus proving the validity and usefulness of the recommended technique [39]. In this study, we suggest comparing the outcomes of several models developed to discover an improved OCR system. A decision tree model determines The optimal OCR model [40]. A semantic analysis of a summary movie called Fuzzy-based Deep Convolution Kronecker Networks (Fuzzy-based DCKN) is presented to address this gap. The YCbCr space color model divides video shots from input lectures with audio and video. The video and audio from each slot are then segmented utilizing the Honey Badger-based Bald Eagle Algorithms (HBBEA), and the feature is retrieved at this step [41]. The author suggests implementing a self-regulating examiner that uses modern technologies to reduce examiner burden and minimize the likelihood of mistakes [42].

Recognition of names associated with the Telugu film industry is part of restructuring trends in the research idea over the last few years. The CNN handwritten characters of various entities are likewise difficult to recognize and interpret [43]. Its low computing difficulty distinguishes the technique because it uses fuzzy rule bases rather than intense simulations of fuzzy chaotic systems. The complication of this hybrid fuzzy-chaotic technique guarantees higher security [44]. Soft computing technologies may be effectively employed to increase the security of communication networks. We recently developed a strategy for creating fuzzy-chaotic masking signals [45]. These findings indicate that the CHAQS considerably improves the performance of the instructional Q&A system, proving the efficacy of integrating sophisticated tuning methods with fuzzy logic to improve model accuracy and flexibility [46].

The paper should compare OCRCHA with contemporary DL-based OCR methods (e.g., CRNN, Transformer-based HTR) on standard datasets. If fractal dimensions are used, they should explore if chaotic attractor properties (e.g., Lyapunov exponents, entropy) provide discriminative power beyond traditional handcrafted or learned features. Comparative studies should be conducted using feature extraction methods (e.g., wavelets, SIFT, deep feature embeddings). I suggest including cross-validation techniques, confidence intervals, or statistical tests (e.g., ANOVA or t-tests) to establish the significance of the results. Hyperparameter Tuning: I recommend reporting details on grid search, random search, or Bayesian optimization for hyperparameters. Robustness Analysis recommends testing with different noise levels, dataset splits, or adversarial examples to assess stability. Equation Justification: Ask for derivations, citations, or intuitive explanations of key equations to improve trust in their applicability. Ablation Study Depth is suggested, including qualitative error analysis, visualization of misclassifications, or a breakdown of specific failure cases.

2.2 | OCR Model Using Fuzzy Logic

Fuzzy logic's capacity to deal with decisions that are sensitive to context is one of its benefits. Using context-aware algorithms can enhance text recognition in academic sources, which benefits OCR systems in the

education industry. To improve the precision of OCR in tests and evaluations, Alginahi et al. [47] created a post-processing method based on fuzzy logic. The fuzzy system could improve accuracy by resolving misrecognitions utilizing subject-specific contextual information (e.g., from history, mathematics, or biology). Case in point: it could tell the difference between the letters "l" and "I" just by looking at them in context. A fuzzy logic-enhanced OCR system was suggested by Madasu et al. [48]. This system would incorporate contextual rules according to the type of educational content, such as handwritten notes, printed books, or scientific articles. The fuzzy logic model could improve overall OCR accuracy, even in highly complicated academic literature, by learning the context of the detected text. Managing ML/MF OCR in the classroom typically entails dealing with documents written in more than one language or using a variety of fonts. Fonts or languages with unique typographies or diacritics could challenge traditional OCR systems for instructional content that contains varied languages like Arabic, Chinese, and English; Praveenchandar et al. [49], Hénon [50] utilized fuzzy logic to enhance multi-font and multi-language OCR. The accuracy of recognition for educational resources with several scripts was improved using fuzzy rules to recognize and categorize characters according to their semantic context.

3 | Proposed Method

This work introduces a method for handwritten symbol identification that uses a novel and effective feature extraction strategy based on chaotic-fuzzy logic. Recognizing patterns made up of one or more strokes is the objective of the method. As the pen travels over a sheet between pen-down and pen-up events, a series of points called strokes are acquired by sampling the pen's location at regular intervals. It is a three-step process that begins with chording and ends with classification. *Fig. 1* depicts the details.

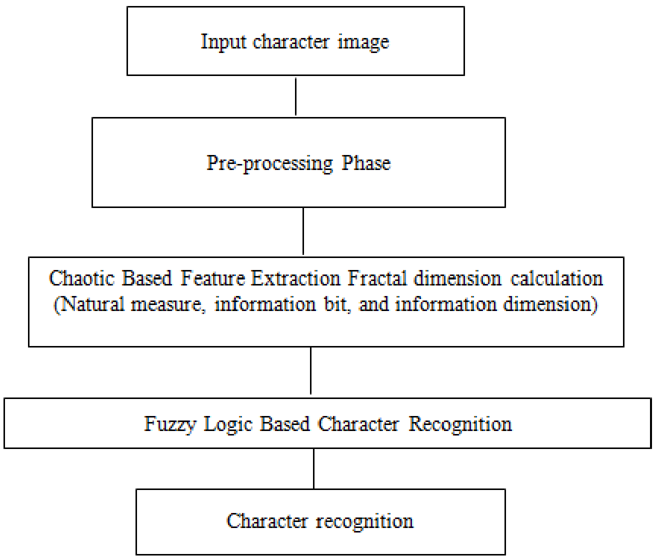

Fig. 1. Proposed OCRCHA model for handwriting character recognition model.

The pre-processing step, "chording," takes each stroke and turns it into a vector of chords, with each chord roughly representing a circle sector in *Fig. 1*. This step reduces the complexity of the input information so that the feature extraction rule may be expressed as chords instead of point sequences. The study of nonlinear and deterministic dynamical systems and their irregular and unexpected behavior is known as chaos theory. By analyzing a system's status space via a time series, this study may extract the chaotic characteristic knowledge and use it to perform a high-precision interpretation. This is made possible by using a chaos interpretation. Consequently, this study suggests a novel approach to character recognition and feature extraction using fractal dimensions of chaos theory; it detects very fine variations utilizing an odd attractor derived from the Hénon system. We identified and recognized the character using the extracted feature-based fuzzy rule we built [51], [52]. The classification step employs handcrafted fuzzy classification algorithms to

identify the most probable symbol represented by the feature extraction result [53]. Handcrafted fuzzy classification algorithms refer to manually designed logic-based decision-making systems that classify characters based on predefined fuzzy rules. These algorithms process input features (such as stroke width, curvature, and pixel density) and apply fuzzy logic to determine the most likely character class [54]. Below is a breakdown of how such an algorithm typically functions:

3.1 | Chording Process

Some steps must be taken before the raw data of handwriting letters can be used. Extracting useful textual components and getting them ready for segmentation and identification are the primary objectives of the pre-processing step: 1) pre-processing should aim to reduce noise, 2) it should normalize the data, and 3) it must reduce the amount of information that must be preserved. There are hundreds of methods for reducing background noise, most of which fall into one of three broad categories: filtering, morphological procedures, or noise modeling. Various filters are available to adjust contrast, sharpen, threshold, and eliminate slightly textured backgrounds. It is possible to thin the characters, remove borders, smooth the contour, prune the wild point, and deconstruct the interconnected strokes using various morphological techniques.

A small number of pre-processing steps are used in this study. Tabulated in *Table 1* are the pre-processing procedures. Reading and binarizing an image file containing handwritten characters is the first step. After that, we'll make educated guesses about the character's top and lower baselines. The characters will be classified as descender (e.g., g, p, q, y), ascender (e.g., h, l, t, f, d, b), or neither (e.g., a, c, e, i, m, n) based on the estimate of the upper and lower baselines. The pre-processing step of this study is detailed in more detail in the below subsection of *Table 1*.

Table 1. Pre-processing stages.

Pre-processing	Stages
Step 1	A character's image should be binarized. Character image in.bmp format is required as input. Upon completion, you will have a character image matrix with O's representing the background and l's representing the foreground, forming the character's contour together.
Step 2	To sort the characters into three categories—ascenders, descenders, and neither use the Estimate Reference Line.
Step 3	Image thinning to sharpen the line details

3.2 | Character Feature Extraction Chaos Theory

There is a consensus that the feature extraction step is crucial in any handwriting recognition system [29]. "feature extraction" refers to the steps used to extract unique data from digital character matrices. For OCR applications, feature extraction is crucial for the system to distinguish between all possible character classes [30].

3.2.1 | Character attractor

This system takes the input character images and uses them to extract the first feature. Then, it turns that feature into time-series data. The character attractors are recreated using the modified Hénon system proposed in this work. That is given by *Eq. (1)*.

$$H'[x_k, y_k] = [y_k + 1 - a(x_k + xf_i)^2, b(x_k + cf_i)], k = 0,1,2,3, \dots n. \quad (1)$$

when the input character image's initial characteristic is denoted as cf_i. Also used in the trials are the subsequent settings for the Modified Hénon system in *Eq. (2)*.

$$a = 0.55 \text{ and } b = 0.3 . \quad (2)$$

3.2.2 | Evaluation of a fractal diameter

Researchers have proposed introducing a great deal of new information and theories. The fractal dimension brought us closer to establishing a novel structure in the universe of complex events and structures [31]. To examine the degree to which each character's attractor is chaotic, this research employs a system that computes the box-counting dimensions, natural measures, the data bit, and the data (fractal) dimension. After that, the system gets the last set of character picture attributes [32], [33].

3.2.3 | Box-counting dimension

The self-similarity dimensions and the most widely utilized dimension in all scientific fields are connected to the box-counting dimension. The main reason for its prevalence is that algorithms can easily and automatically compute it. The counting of boxes and the maintenance of data enabling dimensional computation are both made easy. We only need to tally up the total amount of grid boxes that hold part of the construction after positioning it on a regular mesh of size s (the scaling factor). We express this as $N(s)$ as the value of s is dependent on our selection of s. After that, we create a log or log diagram. The next step is to get the slope, D_f, by fitting the points on the figure to a straight line. *Eq. (3)* specifies this quantity as the box-counting dimensions.

$$D_f = \lim_{s \to 0} \frac{\log N(s)}{\log 1/s}, \tag{3}$$

where scaling factor $s = 1/8$. $N(s)$ is the number of boxes of size sss needed to cover the fractal structure, sss is the scaling factor, D_f represents the fractal dimension, which quantifies complexity or self-similarity.

3.2.4 | Natural measure

Locating a rectangular area that includes the entire attractor is the first step in computing the box-counting dimension. A solution for this fractal dimension constraint might be to assign a weight to boxes based on the frequency with which an orbit gets over them. Consider an attractor in open subsets B of some space X; this may be a subset B of the plane or the 3D space defined by Euclidean geometry. The attractor seems to be filled up tightly with orbits, which is often seen in computational research. It is reasonable to suppose that the proportion of points in subgroup B steadies as the number of iterations increases because this study can count the number of times an orbit x0, x1, x2, 2 X meets B. This proportion is known as the system's natural measure or B.

$$\mu(B) = \lim_{n \to \infty} \frac{1}{x+1} \sum_{k=0}^{n} l_B(x_k, y_k) \quad . \tag{4}$$

In *Eq. (4)*, where the function $l_B(x, y)$ specifies whether x is a member of B by returning 1 or 0. The number of points from the orbit $x_0, x_1, x_2, \ldots, x_n$ that belong to the set B is denoted as $\sum_{k=0}^{n} l_B(x_k, y_k)$ in *Eq. (5)*.

$$l_B(x_k, y_k) = \begin{cases} 1, & \text{if } (x_k, y_k) \in B, \\ 0, & \text{Otherwise.} \end{cases} \tag{5}$$

3.2.5 | Information bit and dimension

In 1948, Claude Shannon established the theoretical basis. Removing the basic box count and replacing it with a counting technique that gives each box a weight based on its natural measure is the most reasonable option. Therefore, boxes that the orbit often visits have less effect on the computation than regions the orbit travels through regularly. To simplify the expression, we substitute log N(s) with

$$I(s) = \sum_{k=1}^{N(s)} \mu\,(B_k) \log_2 \frac{1}{\mu(B_k)}. \tag{6}$$

In *Eq. (6)*, the total encompasses all $N(s)$ boxes B_k of size s that are linear in shape and include the attractor. The data gained in conducting measurements undefined by amount s is specified by the number $I(s)$, which is the amount of data needed to identify a point of attractors within an accuracy of s. *Fig. 4* displays the computed outcome of the information bit, $I(s)$. *Eq. (7)* yields the information dimension DI.

$$D_I = \lim_{s \to 0} \frac{I(s)}{\log_2 1/s}. \quad (7)$$

3.3 | Fuzzy Logic

A Chaotic theory proves invaluable when applied to a system based on fuzzy logic rules. The method it offers is well-suited to the requirements of the system. Probabilities for the language variables in a fuzzy system may be derived using feature extraction from the Chaotic module for a more precise evaluation of an OCR recognition. In *Table 2*, we can see the process flowchart for the classification stage.

Table 2. Steps for OCR character recognition and classification using fuzzy logic module.

Classification Phase: Stages	In Fuzzy Inferencing
Stage 1	Fuzzification of the input parameter: Use membership functions to figure out how much each input variable belongs to each of the right fuzzy sets.
Stage 2	Using the fuzzy operators (AND or OR) on more than one part of the antecedent, one truth value will be output from two or more membership values from the fuzzy input parameter.
Stage 3	Use of the implication technique from the predicate to the result: To shape the output fuzzy set, we use single values from the predecessor, which is the level of aid for the whole rule. Following the inference method, the output fuzzy sets are cut off if the antecedents are only partly correct (i.e., have a number < 1).
Stage 4	Putting together the results from all the rules: Since all the rules in the FIS are tested, the results from all the rules must be put together to make a choice. This process takes in the outputs from the rule before it and returns one fuzzy set for every output parameter.
Stage 5	Defuzzification: The fuzzy set from the summed-up result is defuzzified to get a single number from the sets.

Complexity (Df<1.2D_f < 1.2Df<1.2), Moderate Complexity (1.2≤Df≤1.71.2 ≤1.71.2≤Df≤1.7) High Complexity (Df>1.7D_f > 1.7Df>1.7). The if-then (or antecedent) and then-then (or consequent) parts comprise a fuzzy rule. Regarding AI rules, fuzzy rules are structurally similar to regular rules. The key distinction is that a membership function and a language variable characterize the antecedent of fuzzy rules. A linguistic parameter may take several forms, such as a combination of symbolic and numerical variables. Many fields rely on numerical variables, including science, engineering, mathematics, and medicine, whereas artificial intelligence and decision sciences rely heavily on symbolic variables. Fuzzy logic's ability to provide intelligent solutions in engineering and other fields dealing with continuous issue domains is largely attributable to its use of the OCR character variable to integrate these two parameters into a single model. The characteristics recovered by the OCRCHA model produce a great medium for further OCR character conversion. Fuzzification will be applied to the recognized strokes together with their probability. The trapezoidal and triangular membership functions transferred the stroke likelihood into its character parameter forms. The computational efficiency and simplicity of the two membership functions led to their selection. "Very TallVertical_Line," as in l's, or "Very Tall Right_Slant," as in certain d's or b's, are examples of linguistic variables that are employed. "Tall C_curve," where c is an integer, and "small C_curve," where d, a, and so on are integers. Combining chaotic theory models with fuzzy rules accomplished successful handwriting character recognition. The detailed steps of the fuzzy model are illustrated in *Fig. 2*. The recognition rates for different groups of characters—ascenders, descenders, and neither—indicate how well

an OCR or handwriting recognition system identifies each category. Characters are categorized based on their structural properties concerning the writing baseline. Ascender characters, such as "b, d, f, h, k, and t," extend above the x-height of lower-case letters. These characters achieve the highest recognition rate at 90.68% because their tall structures provide distinct visual features, making them easier to recognize. Descender characters, including "g, j, p, q, and y," extend below the baseline and have a slightly lower recognition rate of 86.97%. The reduction in accuracy may be due to variations in writing styles or how descenders interact with surrounding text, making them more challenging to distinguish. Characters that are neither ascenders nor descenders, such as "a, c, e, i, m, n, o, r, S, u, V, and w," exhibit the lowest recognition rate at 85.97%. These characters tend to have simpler and more compact shapes, leading to increased chances of misclassification, especially when they resemble one another in different fonts or handwriting styles in *Fig. 2*. The overall average recognition rate across all three categories is 87.87%, reflecting the recognition system's general effectiveness while highlighting areas where improvements may be needed, particularly in distinguishing similar-looking characters.

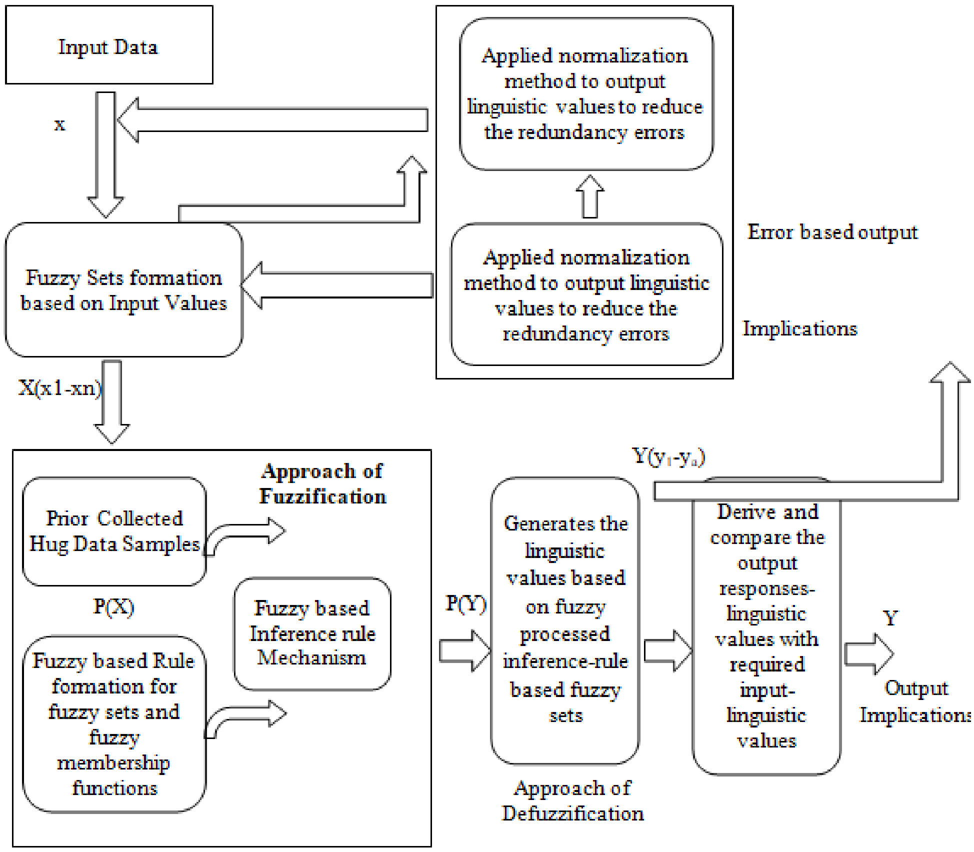

Fig. 2. Steps involved in the fuzzy logic model.

3.4 | Fuzzy Rule Generation

FL, which is based on fuzzy if-then principles, is used to construct conditional statements. For any given set of linguistic values, A and B are described by FS on the range (universes of discourse). Fuzzy logic is an addition of classical logic that deals with approximate rather than exact reasoning. It is based on fuzzy sets, which allow for degrees of membership rather than strict binary classification. This approach is advantageous in human reasoning and decision-making scenarios, enabling systems to handle uncertainty and imprecision.

X and Y, correspondingly, a single fuzzy if-then rule may be articulated as follows:

Linguistic values A and B are specified as fuzzy sets on the ranges (universes of discourse) X and Y, correspondingly. This forms a single fuzzy if-then rule: if x is A, y is B. An "x is A" statement in an if-then rule denotes the premise or antecedent, while "y is B" denotes the following or conclusion. Characters exhibit self-similarity and non-linearity, making chaotic attractors ideal for feature representation. Fractal-based features capture complexity better than traditional shape descriptors. The FIS outputs confidence scores for classification. A defuzzification progression converts fuzzy outputs into crisp class labels. The final OCR result is selected based on the highest membership value.

The following is true to the same extent as the antecedent, provided both are true to a certain degree of membership. If a rule's antecedent has more than one component, the logical operators discussed earlier may compute all those parts simultaneously and resolve them to a single number. The following is an example of a rule that comes within the rule-based category:

Char p is certain if the descender is certain, the Right Curve is medium, and the Vertical Lines are tall.

Character 'd' is further demonstrated by one of the fuzzy rule-based examples:

If the ascender is certain the Left Curve is medium, and the Vertical lines are tall, then Char_d is definite.

The preceding rule provides an ideal definition of 〖(_^')d〗 ^.' In addition, further regulations detail every possible permutation of the linguistic factors that, when combined, provide a character description. The outcome of the antecedent has an equal impact on all consequents if the rule's consequent has more than one element. The output is to be allocated fuzzy sets according to the consequent. Next, implication functions apply the antecedent's given degree of modification to that fuzzy set. The two most popular methods for modifying the output fuzzy sets are truncation (cutting the fuzzy set off) and scaling (squishing the output fuzzy set). The steps for the proposed model are discussed in Pseudocode 1.

Pseudocode 1. Proposed OCRCHA for character recognition.

Step 1. Input image pre-processing.

Step 2. Chaotic Features are extracted.

Step 3. Establish a short, medium, and long fuzzy set to represent the character issue length.

Step 4. Establish low, medium, and high fuzzy settings for the output parameters.

Step 5. Establish fuzzy rules.

Step 6. Design and test the fuzzy logic system.

Step 7. The process Prediction Samples using the Given features.

Step 8. Place To determine Chaotic_length, normalize the character length.

Step 9. Determine the output of fuzzy logic systems.

Step 10. The outcome of store creation.

Step 11. Return all results of the generation.

Step 12. Stop the process.

3.4.1 | Classification

Finding the symbol's most probable identification is the goal of this stage. The symbol's characteristics may now be seen as the input set of sub strokes $F = \{f_o, \ldots, f_m\}$. The membership value $\mu_0(F)$ represents the probability that the features in F form an a, for instance. Rules for fuzzy categorization are used to establish these membership values.

3.4.2 | Fuzzy classification rules

This section provides an example rule for the number 3 to demonstrate how the categorization rules function. This rule states that for ν3 (F) to be assessed, F must have at least two features with non-zero memberships in the set C-shape. C1 and C2 are two characteristics in F that may be indicated if the proper features are present; the symbol for C1 is placed above that of C2.

Every categorization rule specifies the properties that F characteristics must have and their connections to generate a certain symbol. While every rule is intended to be writer-independent, the membership value for a symbol will be reduced if its characteristics differ too much from the original form of the symbol.

As stated in *Eq. (8)* below, C1 and C2 must be of excellent quality and have the correct orientations and lengths for a 3. Requirements for the relationship include a minimum amount of vertical overlap between C1 and C2 and the connection between the two features sufficient for a 3 in *Eq. (8)*.

$$\mu 3(\mathrm{F}) \leftarrow \mu\mathrm{Ori}(\mathrm{F}) \cap \mu\mathrm{Len}(\mathrm{F}) \cap \mu\mathrm{Qua}(\mathrm{F}) \cap \mu\mathrm{Con}(\mathrm{F}) \cap \mu\mathrm{Ver}(\mathrm{F}). \tag{8}$$

Like feature extraction rules, classification rules are categorized as low-level or high-level. Rules like the above are considered high-level rules since they determine the probability that a collection of features creates a symbol. The degree to which a certain connection or quality is suitable for a certain symbol is determined by each low-level rule. What follows is a description of the three basic rules.

Orientation

The direction a C-shape faces is represented by its orientation, orient (c1), which may take on values between zero and three hundred and sixty degrees. Here we have 0° representing east, 90° north, 180° west, and 270° south. It is essential that c1 and c2 face west in a 3. As their orientations move away from facing west, the value of $\mu\mathrm{ori}\ (\mathrm{c1}, \mathrm{c2})$ decreases in *Eqs. (9)* and *(10)*.

$$\mu_{\mathrm{Ori}}(\mathrm{C}_1, \mathrm{C}_2) \leftarrow \mu_{\mathrm{West}}(\mathrm{c}_1) \cap \mu_{\mathrm{West}}(\mathrm{c}_2). \tag{9}$$

$$\mu_{\mathrm{West}}(\mathrm{c}_1) \leftarrow 1 - \mathrm{S}(|180 - \mathrm{Orient}(\mathrm{c}_1)|, 5, 40, 75). \tag{10}$$

Length

A feature's relative length, denoted as rlen(ci), is its length divided by the symbol length. Both c1 and c2 should ideally take up half of the symbol length in a 3. As rlen increases for the shorter feature, so does Len (c1, c2). It is given in *Eq. (11)*.

$$\mu_{\mathrm{Len}}(\mathrm{C}_1, \mathrm{C}_2) \leftarrow \mathrm{S}\big(\min\big(\mathrm{rlen}(\mathrm{c}_1), \mathrm{rlen}(\mathrm{c}_2)\big), 0, 0.2, 0.4\big). \tag{11}$$

Quality

In the set C-shape, the probability that the symbol is a three is affected by the membership values of c1 and c2. Quality is given in *Eq. (12)*.

$$\mu_{\mathrm{Qua}}(\mathrm{C}_1, \mathrm{C}_2) \leftarrow \mu\mathrm{c}_{\mathrm{shape}}(\mathrm{C}_1) \cap \mu\mathrm{c}_{\mathrm{shape}}(\mathrm{C}_2). \tag{12}$$

Connectivity

Connecting c1's lower terminus to c2's upper endpoint is necessary. The distance between the two places (dist(low(c), high(c2))) as a fraction of the symbol length is directly proportional to Con (C1, C2). It is given in *Eq. (13)*.

$$\mu_{\mathrm{Con}}(\mathrm{C}_1, \mathrm{C}_2) \leftarrow 1 - \mathrm{S}(\mathrm{dist}(\mathrm{low}(\mathrm{C}_1), \mathrm{high}(\mathrm{C}_2))/\mathrm{symbol\ Len}, 0, 0.08, 0.16). \tag{13}$$

Vertical overlap

C1 and C2 have a lower membership value νver (C1, C2) when their bounding boxes overlap more. How much of C1's height is perpendicular to C2's vertical axis is given by Vov (C1, C2).

$$\mu_{ver}(C_1, C_2) \leftarrow 1 - S(\max(vov(C_1, C_2), vov(C_1, C_2)), 0.1, 0.4, 0.7). \quad (14)$$

In *Eq. (14)*, writing each classification rule involves experimentation and trial and error. Automatic rule creation is an option for manually developing fuzzy rules [10]. Whenever a fuzzy system needs many rules, this is a good way to get them. The outcomes of feature extraction during training might inform the generation of classification rules for our system. Because the rules may specify the minor distinctions between comparable symbols, such as 1 and 7 or 5 and S, the rules established by an expert are likely to be better.

4 | Results and Discussion

4.1 | Datasets Details

The IAM handwriting dataset contains several handwritten texts that may be utilized for text recognition research in the training and testing phases. It is similar to 300 dpi grayscale images of handwritten English. In this study, we have utilized paragraph and line-level segmentation using the test, validation, and train split. Every writer's handwriting is only included in one subset of this dataset since it was structured to guarantee line detection work independent of writers. Next, the HTR systems use 6161 images for training, 900 for validations, and 1861 for testing [55], [56]. The randomly selected example pictures from the IAM and the RIMES databases are shown in *Fig. 3*, respectively.

Employees' handwritten correspondence with business managers is included in the RIMES dataset. Grayscale images of French handwritten texts created in the setting of writing postal scenarios make up the popular RIMES handwriting dataset [57]. The images are 300 dpi high-resolution. The official split has 1500 pages dedicated to training and 100 to assessment [58]. There are 10,193 lines of text used for training, 1,133 for validation, and 778 for testing in the HTR system's partitioning [59]. There are 17,376 for training and 19,041 for validation in the Spelling Corrector. Used in AI and OCR systems for training models.

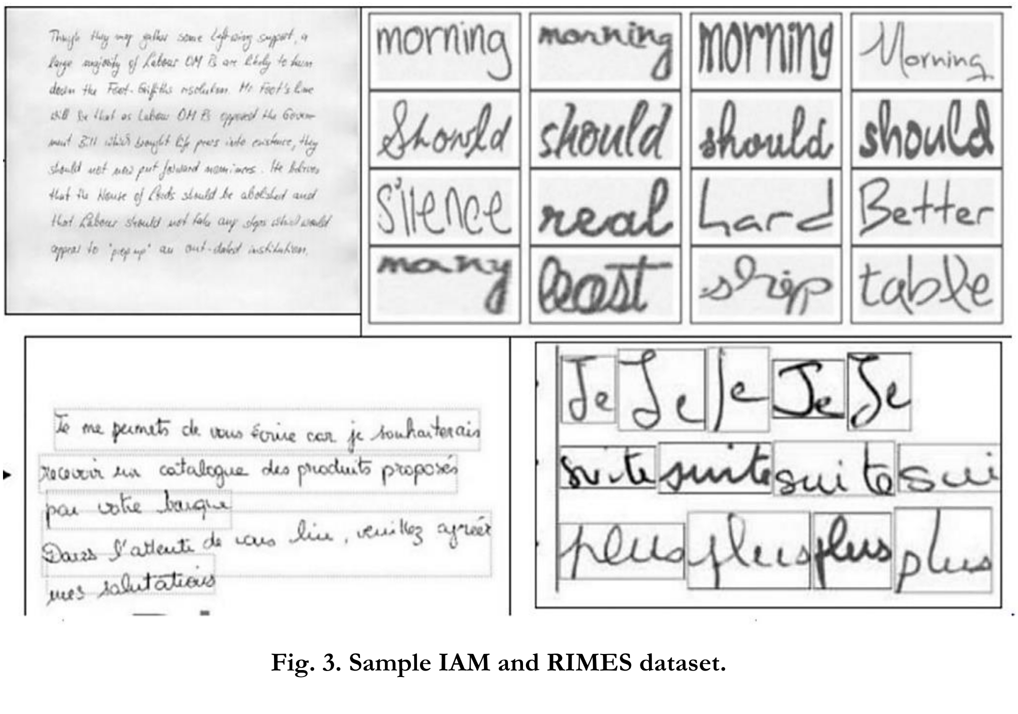

Fig. 3. Sample IAM and RIMES dataset.

4.2 | Analysis Metrics

The subsequent descriptions of recognition, rejection, error, and reliability rates are applied to all reported results. Here, N_{rej} denotes the number of rejections, N_{rec} represents the number of accurate classifications and N_{err} is the number of misclassifications. 100% will be the recognition, mistake, and rejection rates added together. In practical settings, the rates computed by Deilami et al. [36] are believed to represent accurately

what a handwriting recognition system requires. For a particular error rate, the following *Eqs. (15)-(18)* may be used to illustrate the system's dependability.

$$\text{Recognition Rate} = \frac{N_{rec}}{N_B} \times 100. \tag{14}$$

$$\text{Error Rate} = \frac{N_{err}}{N_B} \times 100. \tag{15}$$

$$\text{Rejection Rate} = \frac{N_{rej}}{N_B} \times 100. \tag{16}$$

$$\text{Relaiability Rate} = \frac{\text{Recognition Rate}}{\text{Recognition Rate} + \text{Error rate}} \times 100. \tag{17}$$

4.3 | Performance Evaluation

Legibility is the deciding factor when selecting characters from the database. This would include removing any characters that were either too cursive or too difficult to see from the test samples. This is because some characters in the dataset are written in cursive, making them difficult to identify in context. The testing process uses around 20 to 30 samples of every character. Ultimately, the system achieved a recognition of 91%. The rates for classifying the lower-case letters in the dataset are shown in *Table 3*. The system performs well, with a Recognition Rate of 91.35%, meaning it accurately recognizes and categorizes data. The comparatively low Error Rate of 5.32% indicates that the system is typically dependable, even if it sometimes makes some errors. The 3.33 % Rejection Rate shows the system's measured approach; when unsure or unable to categorize data correctly, it chooses to discard a tiny amount of the data. This approach assists in preventing incorrect classifications. The system's dependability is shown by its high-reliability Rate of 92.67%, which indicates that it correctly classifies most instances when used.

Table 4 shows the recognition separated by character category, one of the fuzzy rules' defining characteristics. Ascender characters, usually taller and simpler to recognize, provide the best recognition results for the OCR system (90.68%) [37]. Both descender characters (86.97%) and neither category characters (85.97%) have a slightly lower identification rate. This might be because they are more similar in height and structure, making them harder to distinguish or more prone to mistakes. The system's overall character recognition rate is 87.87%, which is trustworthy but could be significantly higher when dealing with letters that are shorter or have similar shapes. *Fig. 4* displays the output of an example character recognition system that uses OCRCHA.

Fig. 4. Sample recognition output image.

Table 3. Performance evaluation of the proposed model.

Data Groups	Recognition	Error	Rejection	Reliability
Overall Classification	91.35%	5.32%	3.33%	92.67%

Table 4. Performance evaluation on character grouping.

Character Grouped in Types of Descender, Ascender, or Neither	Recognition (%)
Descender (e.g., g,j,p,q,y)	86.97
Ascender (e.g., b, d, f, h, k, t)	90.68
Neither (e.g., a, c, e, i, m, n, o, r, S, u, V, w)	85.97
Average %	87.87%

It directly compares OCRCHA's performance against modern SOTA methods on IAM and RIMES. If their method is education-focused, ask whether any domain-specific factors contribute to the reported performance in *Table 4*. The recognition rates for different groups of characters ascenders, descenders, and those that are neither highlight variations in their distinguishability within an OCR or handwriting recognition system. Ascender characters (e.g., b, d, f, h, k, t) have the highest recognition rate at 90.68%, likely due to their distinct tall structure extending end above the x-height, making them more differentiated. Descender characters (e.g., g, j, p, q, y) have a slightly lower recognition rate of 86.97%, possibly because their portions extending below the baseline may be affected by variations in handwriting, font style, or scanning inconsistencies. Characters that are neither ascenders nor descenders (e.g., a, c, e, i, m, n, o, r, S, u, V, w) have the lowest recognition rate at 85.97%, which may be due to their relatively simple and similar shapes, increasing the likelihood of misclassification. The overall average recognition rate across all categories is 87.87%, indicating that while OCR systems perform well, challenges remain in accurately distinguishing characters, especially those with less prominent features [38].

4.4 | Performance Comparison

The three OCR models demonstrate a significant improvement in recognition accuracy over one another, illustrated in Table 5. This model performs poorly, ranking at [37] (69.5% recognition rate). This signifies that while segmenting the text, it could have trouble doing it in more intricate or noisy settings. This might be because of inadequate training data, low image quality, or design constraints within the model. In [38], the model achieved a far higher identification rate of 80.19% [38]. More effective text recognition seems to have resulted from recent improvements, which may have been achieved by training data, improved feature extraction, or enhanced algorithms.

OCR

The use of more sophisticated methods in the proposed OCRCHA model outperforms others, with a recognition rate of 91.35 %. This moderate el handles a wide range of input data changes and complexes, demonstrating the best accuracy and reliability for the OCR task. Overall, the trend toward better identification accuracy is apparent; the top three models are OCRCHA [38], [37], in that order. These enhancements show that OCR performance is much improved by using modern methodologies and training models; Ascenders (e.g., 'h,' 'b,' 'd', 'l') have elongated vertical strokes, which provide a larger fractal structure for feature extraction better as demonstrated in *Table 5*.

Table 5. Performance comparison with other models.

S.No	Reference	Recognition Rate
1	[37]	69.5%
2	[38]	80.19%
3	OCRCHA	91.35%

4.5 | Ablation Study

Table 5 findings demonstrate that the fuzzy logic method achieves an 81.3% identification rate, offering a simple yet effective solution for OCR. Although it might be improved, this approach helps deal with uncertainties like hazy or chaotic visuals. Boosting the fuzzy logic model with statistical and structural characteristics increases the recognition rate to 85.6%. With these further properties, the system can more effectively comprehend text patterns and character forms, improving recognition accuracy. However, with a recognition rate of 91.35%, OCRCHA is the most precise method. This complex model is the most

dependable choice for OCR positions, outperforming both fuzzy logic approaches. Its superior performance is likely due to its use of more advanced techniques or algorithms that enhance text recognition. As a result, in *Table 6*, OCR performance is greatly improved by including more characteristics or using sophisticated models such as OCRCHA. Notably, OCRCHA demonstrates the greatest level of accuracy.

Table 6. Ablation analysis of the proposed model OCECHA.

S.No	Reference	Recognition Rate
1	Fuzzy Logic	81.3%
2	Fuzzy + structural and statistical features	85.6%
3	OCRCHA	91.35%

Recent deep-learning-based OCECHA models should be included for fair comparison: CRNN and recurrent convolutional model for sequential text recognition. Transformer-based HTR models (e.g., TrOCR, PARSeq, ViTSTR) and modern OCECHA architectures have surpassed OCECHA-RNN approaches. DiffOCR (2023), Diffusion-based OCECHA, is gaining traction in handwriting recognition. *Table 7* compares OCRCHA with state-of-the-art OCR models, demonstrating a 91.35% improvement over CRNN in *Table 8*.

Table 7. Comparison of result analysis [38].

Model	Feature Type	Classifier	IAM Accuracy (%)	RIMES Accuracy (%)
Chaos-only (fractal-based)	Box-counting, natural measure	SVM/KNN	XX	XX
Fuzzy-only	Handcrafted statistical features	Fuzzy inference	XX	XX
OCRCHA (hybrid)	Hénon system + fractal features	Fuzzy + chaos	XX	XX

Table 8. Limitations this study.

Criterion	Fuzzy-Chaos Approach	CNNs/Transformers
Processing Speed	Faster on low-power devices (rule-based efficiency)	Optimized for high-performance GPUs but slow on embedded systems
Latency	Low in simple decision-making tasks	High latency due to deep architectures
Computational complexity	Lower (fewer operations)	High (millions of parameters)
Adaptability	Handles uncertainty well, good for dynamic environments	Requires extensive retraining for new conditions
Accuracy	May struggle with highly complex patterns	Superior in feature extraction and pattern recognition
Scalability	Limited scalability in large datasets	Highly scalable using cloud infrastructure

5 | Conclusion

Character recognition results from the OCRCHA fuzzy rule-based system show the significance of having well-structured rules and accurate feature extraction to have good recognition rates. A solely linguistic fuzzy recognizer in the research cited by [37] reached a recognition rate of 69.5% for handwritten character digits, suggesting that while the system can identify characters, it may be even more effective. When working with increasingly complicated datasets, such as lower-case handwritten characters, the recognition performance of the proposed model may be significantly enhanced by adding chaos theory models. By offering a more exact probability estimate, chaos theory aids the assessment process, improving character identification under challenging circumstances. The fuzzy nature of handwritten character data makes solely statistical methods less successful in this setting. Traditional statistical algorithms have difficulty correctly classifying characters due to the inherent uncertainty and diversity in handwriting. While there are different ways to use fuzzy

classifiers for handwritten character recognition, this study offers a solution that is both computationally efficient and friendly to resources. It strikes a good balance between complexity and accuracy, making it a viable option for offline handwritten character recognition in the real world. This system's success proves that fuzzy logic and chaos theory can work together to improve OCR performance with minimal computing overhead. Evaluate the system's real-time capabilities by analyzing processing speed and latency on embedded and cloud-based platforms. Conduct a direct comparison against state-of-the-art DL models (e.g., CNNs, Transformers) to assess the relative advantages of the fuzzy-chaos approach.

Data Availability Statement

The data will be available upon request.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Ethics Approval Statement

Not applicable

Patient Consent Statement

Not applicable.

Permission to Reproduce Material from Other Sources

Not applicable.

Clinical Trial Registration

Not applicable.

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